

ESTIMATION OF SOIL PARAMETERS FOR ASSESSING POTENTIAL WETNESS: COMPARISON OF MODEL RESPONSES THROUGH GIS

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ABSTRACT

A geographic information system (GIS) is utilized to model wetness potential for a portion of Uwharrie National Forest, North Carolina. The wetness index is derived from TOPMODEL, a hillslope-scale runoff simulation model. The wetness index is a distributed-parameter model, with the input parameters obtained from a digital elevation model (DEM) and Soil Conservation Service (SCS) soils data. The primary objectives of the research are to: (1) compare methods of estimating soil parameters for input into the wetness potential model; and (2) determine how the model outputs vary spatially as a consequence of different methods of estimating soil parameters. Three methods of estimating soil parameters are used: (a) assuming uniform soil properties; (b) using SCS data presented as ranges; and (c) using alternative literature-based estimates of soil parameters. Results indicate that the wetness model responds similarly regardless of how the soil parameters are estimated, but differences in the spatial variability of the wetness potentials occur as a result of estimating soil parameters through alternative approaches. Correlation, pair-wise regression and analysis of regression residuals are used to compare model responses within a GIS environment.

KEY WORDS wetness potential; estimating soil parameters; mapping regression residuals; geographic information systems

INTRODUCTION

Geographic information systems (GIS) are being used increasingly to model biophysical processes, landscape characteristics and feature distributions (Walsh *et al.*, 1990; Davis and Dozier, 1990; Moore *et al.*, 1991; Joao and Walsh, 1992). GIS technologies are characterized by data organized within a spatial coordinate system, by hardware and software systems used to encode, store, retrieve, manipulate and display spatial information, and by a set of analytical tools and techniques used to integrate disparate data for model building and spatial analyses (Goodchild, 1992). To support such activities, a significant amount of geographic data are available in digital form or represented on maps and tabular arrays that can be transformed into digital formats for entry into geographic databases. In this research, a GIS is used to support the calculation of a distributed model of topographic wetness potential by integrating a digital elevation model (DEM) with Soil Conservation Service (SCS) maps of soil types encoded into the GIS. The data are manipulated to derive wetness index values for individual 30 m × 30 m cells that represent Land Management Area 1 of the Uwharrie National Forest, North Carolina. The GIS is also used to generate maps of wetness potential for the study area given the site characteristics derived from the topographic and soils information for each cell and integrated employing the model algorithms. The basic intent of the research is to examine the spatial variability in model responses generated as a consequence of using several approaches to estimate soil parameters for the derivation of the wetness index.

The wetness index used in this research is derived from TOPMODEL, a hillslope-scale runoff simulation model developed by Beven and Kirkby (1979). TOPMODEL estimates saturated subsurface flow using

rainfall data and incorporates measured values of surface slope, runoff area, soil depth and soil hydraulic conductivity. TOPMODEL can be transformed into a 'relative' wetness potential index by assuming uniform rainfall throughout a study area. The wetness index is effectively implemented within a GIS environment, because existing data representing soil type and related physical characteristics (e.g. texture and permeability) can be combined with topographic information for model parameterization.

Because several of the soil variables used to compute the wetness index can be estimated through a variety of approaches, spatial variability is introduced into the results of the model as a consequence of its distributed nature and the methods used to estimate soil variables for computations of the model. This research seeks to define and compare differences in the derived values of the wetness index that occur when different methods of estimating parameters are employed in the computation of the model. Differences in the spatial pattern of the model outputs for a number of variable estimation alternatives are examined through cartographic mapping approaches contained within the GIS and quantitative approaches used to calculate the variability between model outputs. Pearson's correlation coefficients, used to compare derived maps of the wetness index, and regression analyses are used, in a pair-wise fashion, to generate regression residuals between map comparisons. The derived maps illustrate the spatial variation that results from calculating the wetness index with different input parameters as estimated through different approaches. The quantitative analyses assess the degree and nature of the differences which are apparent in the maps of the wetness potentials.

This research evaluates three methods of representing soil data in the GIS for use in deriving a model of wetness potential on a cell-by-cell basis throughout the study area. Differences in the outcomes of the derived wetness index are generated depending upon the manner of soil parameter estimation. The first trial involves the characterization of soil parameters that are expressed in the soil survey as ranges of nominal data—minimum, median or maximum values. The second trial uses a set of soil characteristics assumed uniform in spatial distribution throughout the study area, thereby eliminating soil information in the calculation of the index and relying solely upon topographic information for calculation of the model. In the third trial, differences in the performance of the model are compared when soil values are acquired from SCS estimations versus literature-based estimates of soil parameters. The research is designed to examine the spatial variations in model outputs that result from alternative approaches of estimating soil parameters. When modelling earth surface processes, the approaches used to estimate model variables can affect the performance and sensitivity of the model responses (Walsh *et al.*, 1994).

WETNESS INDEX

Beven and Kirkby (1979) initially developed TOPMODEL to simulate single-event saturation and infiltration runoff within small catchments. The major application of TOPMODEL is to predict hydrologic responses in ungauged basins (Wood *et al.*, 1988; Romanowicz *et al.*, 1993). Variations of the TOPMODEL index have been widely used to produce measures of potential wetness based upon topographic position (Moore *et al.*, 1991). O'Loughlin (1986) derived a similar index to identify surface saturation zones within catchments. Phillips (1990) used a variation of the indices developed by Beven and Kirkby (1979) and O'Loughlin (1986) as a tool to identify and map wetlands in North Carolina. Wolock (1988) and Wolock *et al.* (1989) incorporated the wetness index into a study of the effects of surface water acidification within forested catchments, and Brown (1992) used the index to estimate relative availability of soil moisture in the spatial modelling of vegetation distributions along the alpine treeline ecotone.

Wetness indices are increasingly being integrated into GIS. Romanowicz *et al.* (1993) incorporated TOPMODEL into a water information system (WIS), as a four-dimensional GIS database for manipulating digital terrain models and hydrologic time-series. Band and Wood (1988) integrated TOPMODEL into a GIS for large-scale hydrologic simulation in western North Carolina. Phillips (1990) noted the value of modelling the index within a GIS for a range of applications relating to mapping and determining planning strategies for wetlands, whereas Brown (1992) conducted his alpine treeline research within a GIS environment. For this research, the wetness index was calculated for a portion of the Uwharrie National Forest,

North Carolina, as part of a larger project to model environmental gradients associated with the location of rare and endangered plant species.

The model used in this research is derived from the saturation excess runoff component of TOPMODEL (Wood *et al.*, 1988; Wolock, 1988; Phillips, 1990). TOPMODEL is transformed into a soil moisture potential index by assuming uniform rainfall conditions within a defined geographic region. Where the study area is small in geographic extent and relatively uniform in its topographic variation, controlling for rainfall variation is a commonly employed assumption in soil moisture modelling. This assumption, however, can significantly impact the outcome of the index calculation. The study area for this research was sufficiently small (4580 ha) that the assumption of uniform rainfall, as averaged over time, was deemed appropriate.

The index used in this research follows the form of TOPMODEL employed by Wolock (1988) and Phillips (1990):

$$WT = \ln [A/(T \tan B)] \quad (1)$$

where WT = wetness index (soil moisture potential for a given location), A = surface area drained through a defined landscape unit (30 m \times 30 m cell), T = soil transmissivity and B = surface slope (tangent). For saturated soil conditions, transmissivity (T) can be estimated as the saturated soil hydraulic conductivity (or permeability) of a soil relative to the water table or some confining layer, such as an impermeable pan or bedrock (Phillips, 1990). Equation 1 assumes constant soil hydraulic conductivity throughout the soil

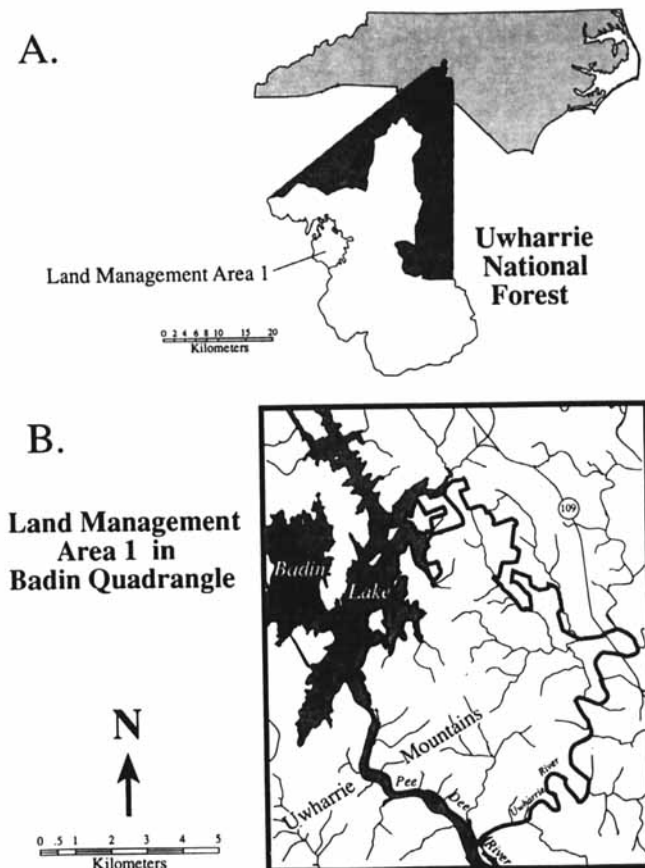


Figure 1. (A) Location of Uwharrie National Forest, North Carolina; (B) Management Area 1, Badin, North Carolina quadrangle

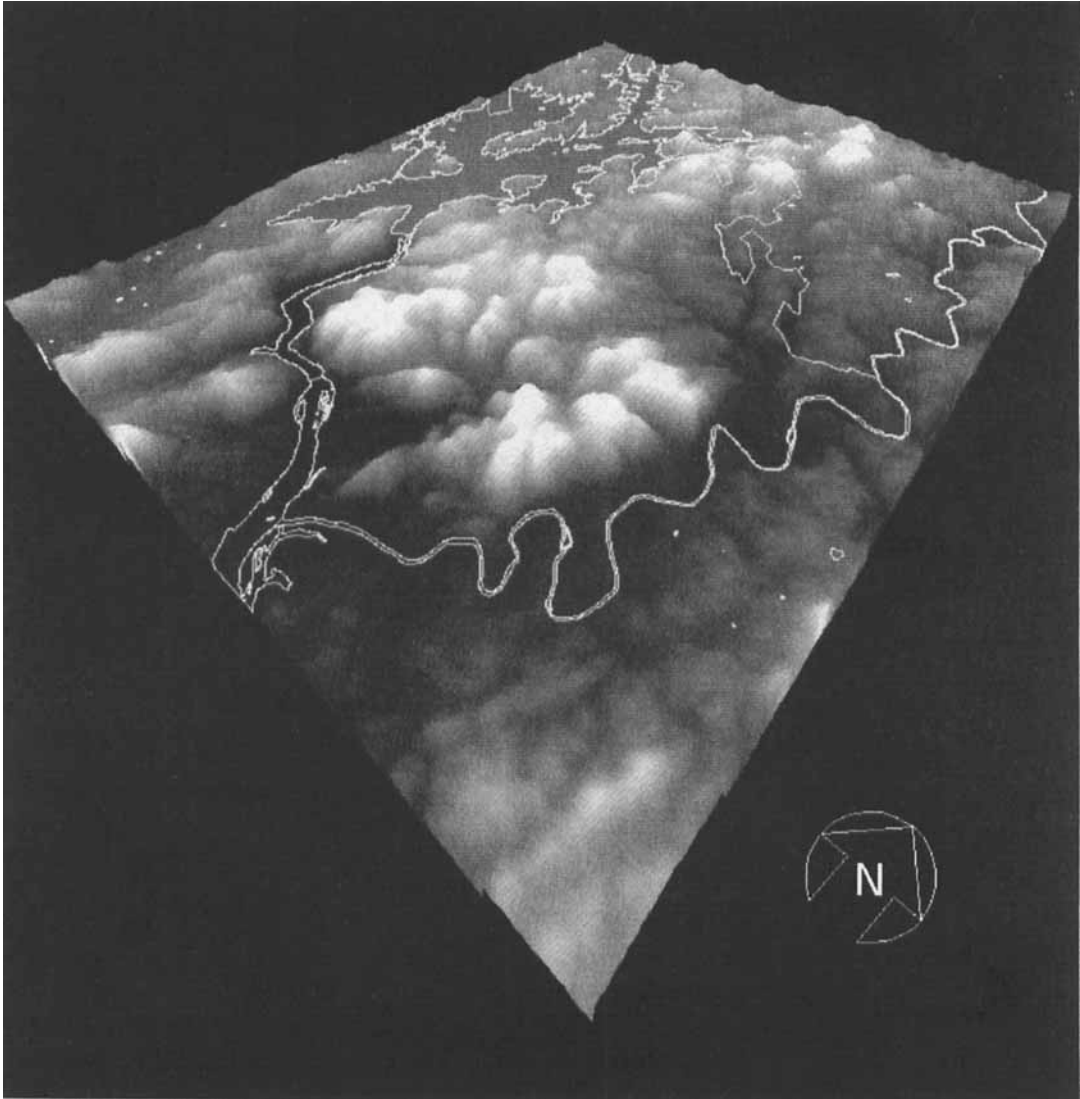


Figure 2. Digital elevation model (DEM) of Land Management Area 1 ($4\times$ vertical exaggeration, 10° altitude angle, and 140° azimuth angle)

profile to a given soil depth, where transmissivity (T) is represented as:

$$T = kd \quad (2)$$

where k = soil hydraulic conductivity and d = soil depth. Soil texture, however, is rarely uniform throughout the soil profile, and if data are available regarding permeability at different soil depths, the transmissivity expression can be modified as:

$$T = \sum_{d_{\max}} (K_i D_i) \quad (3)$$

where K_i = hydraulic conductivity of each horizon i of the soil above the confining layer, D_i = thickness

of each horizon i and d_{\max} = maximum depth of the soil to the confining layer. The variation of horizon characteristics is addressed spatially among soil types, but not within a given soil type. The wetness index, as used in this research, can then be expressed as:

$$WT = \ln \left[A / \left(\sum_{d_{\max}} K_i D_i \right) \tan B \right] \quad (4)$$

Using Equation 4, the wetness index can be calculated in a raster-based GIS environment. The wetness index (WT) is implemented as a distributed-parameter model in which an index value is calculated for every cell within the study area. The GIS is used to manage the information, provide for the spatial registration of the soil and topographic data layers, and as the interface between the model and the spatial data.

Calculations of the wetness index produce values that indicate wetness potentials across geographic space. The pattern of the index values and the spatial variability of potential wetness throughout the study area is represented through a grid matrix in the GIS, with each cell representing $30 \text{ m} \times 30 \text{ m}$ on the landscape. The data used for the calculations were derived from DEMs (elevation, slope aspect, slope angle and curvature/convexity) and digitized soil information (type and characteristics) initially represented at a base-scale of 1 : 24 000. As used in this research, the index is applied as a measure of relative wetness.

STUDY AREA, DATA SOURCES, AND DATA DEVELOPMENT

The study area of the project is Land Management Area 1 of the Uwharrie National Forest, North Carolina (Figure 1A). The study area is located within the Piedmont physiographic province, covers approximately 4580 ha in area, and is contained entirely within the Badin USGS 7.5 minute quadrangle (Figure 1B). The region is characterized by rolling hills in the north portion of the study area and rugged terrain in the south associated with the Uwharrie Mountains (Figure 2). Elevations range from 85 to 300 m above mean sea level. The study area is bounded on the west by Badin Lake, on the south by the Yadkin River, and on the east by the Uwharrie River. The soils are generally deep and loamy, and are formed on rhyolite, argillite, slate, and some intermediate and mafic crystalline bedrock geology (Conley, 1962). A mix of hardwoods, especially oak species (e.g. *Quercus montana*, *Q. stellata*, *Q. velutina*, *Q. alba*) and hickory species (e.g. *Carya glabra*, *C. ovata*), and pine species (e.g. *Pinus echinata*, *P. virginiana*) predominate in the study area. Long-leaf pine (*P. palustris*), rare sunflowers (*Helianthus schweinitzii*, *H. laevigatus*), and other rare or threatened species are present throughout the region.

The base data assembled for inclusion into the GIS were secured from 1 : 24 000 scale USGS DEM for Badin, North Carolina, and from 1 : 24 000 scale soils maps prepared by the SCS. Table I describes the input variables and sources used to model soil moisture potential through the wetness index.

The DEM was preprocessed to correct systematic topographic inconsistencies in the elevation data matrix by smoothing spurious pits and peaks. Surface slope angle and drainage area variables were calculated from the digital elevation model. Surface slope angle identifies the maximum rate of change in elevation for each cell in relation to its neighbours (defined as a 3×3 cell region). Drainage area was calculated using modules present in the ARC/INFO GRID software used in this research. GRID uses a method described by Jenson and Domingue (1988) to calculate drainage area for each cell by deriving the flow direction for each cell

Table I. Geographic database elements assembled to support the calculation of the wetness index

| Variable | Source | Data type | Initial scale |
|-------------------|--------------------------|-----------|---------------|
| Surface slope | USGS DEM | Digital | 1 : 24 000 |
| Drainage area | USGS DEM | Digital | 1 : 24 000 |
| Soil types | Digitized from SCS maps | Analogue | 1 : 24 000 |
| Soil depth | SCS soil interpretations | Analogue | 1 : 24 000 |
| Soil permeability | SCS soil interpretations | Analogue | 1 : 24 000 |

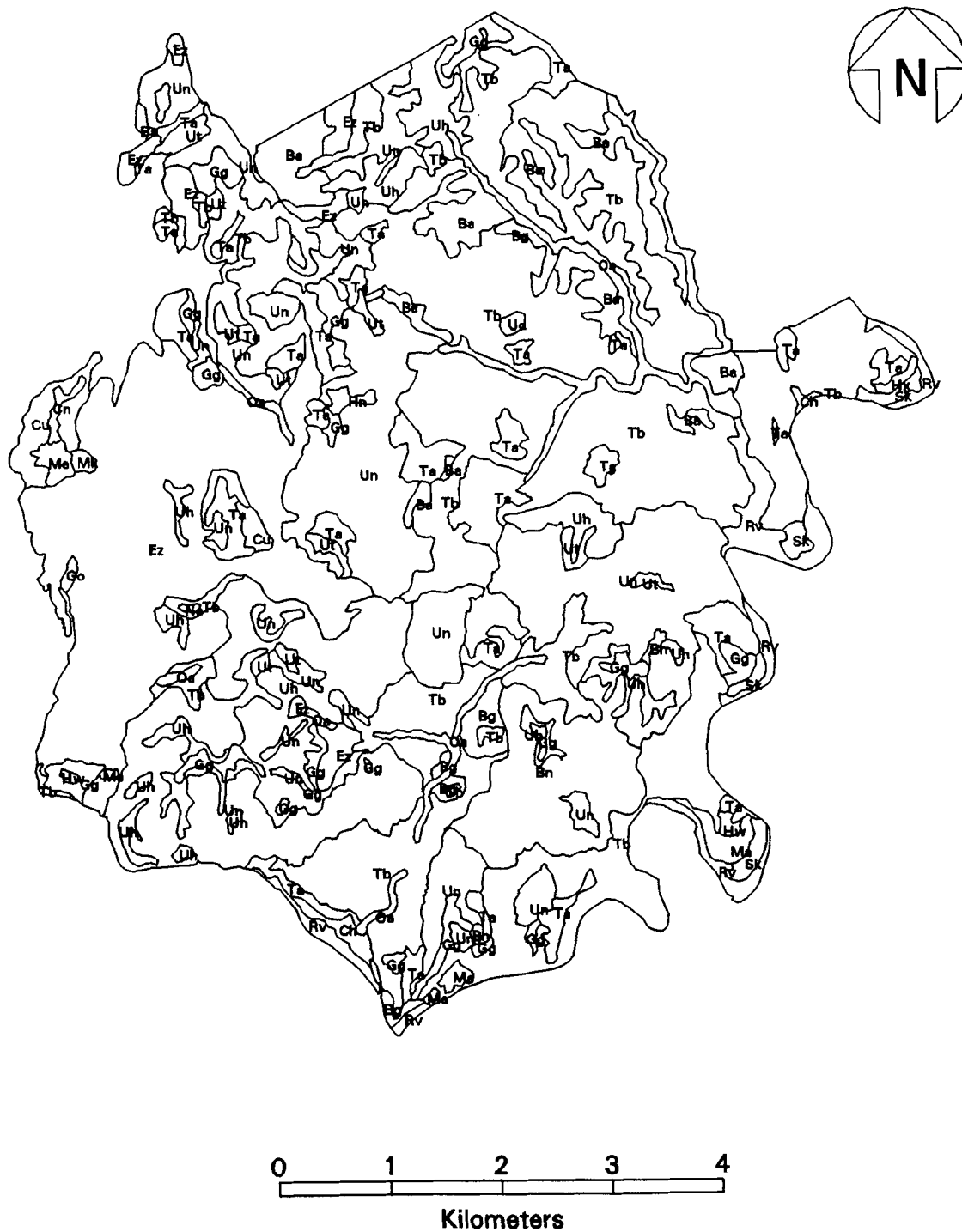


Figure 3. Soil map of the study area (see Table II for soil names of mapping units)

Table II. Soil characteristics derived from SCS soil interpretations. The values used for the soil complexes are derived from the extremes of the individual soil types

| Soil series | Horizon depth (cm) | Permeability (cm h ⁻¹) | Bedrock depth (cm) | Water table depth (cm) |
|---|--------------------|------------------------------------|--------------------|------------------------|
| Badin channery silt loam (Ba) | 0-64 | 1.52-5.08 | 51-102 | >183 |
| Badin-Goldston complex (Bg) | 0-102 | 1.52-15.24 | 25-102 | >183 |
| Badin soil (50%) | | | | |
| Goldston soil (35%) | | | | |
| Badin-Nason complex (Bn) | 0-127 | 1.52-5.08 | 51-152 | >183 |
| Badin soil (45%) | 127-152 | 0.0-0.15 | | |
| Nason soil (40%) | | | | |
| Chewacla silt loam (Ch) | 0-147 | 1.52-5.08 | >152 | 15-46 |
| Cullen clay loam (Cu) | 0-183 | 1.52-5.08 | >152 | >183 |
| Cullen loam (Cn) | 0-23 | 5.08-15.24 | >152 | >183 |
| | 23-183 | 1.52-5.08 | | |
| Enon-Zion complex (Ez) | 0-25 | 1.52-15.24 | 51->152 | >183 |
| | 25-152 | 0.15-0.51 | | |
| Enon soil (60%) | 0-20 | 1.52-15.24 | >152 | >183 |
| | 20-28 | 1.52-5.08 | | |
| | 28-84 | 0.15-0.51 | | |
| Zion soil (30%) | 0-25 | 1.52-15.24 | 51-102 | >183 |
| | 25-66 | 0.15-1.52 | | |
| | 66-91 | 0.51-5.08 | | |
| | 91-102 | 0.0-0.025 | | |
| Georgeville silt loam (Gg) | 0-160 | 1.52-5.08 | >152 | >183 |
| Goldston channery silt loam (Go) | 0-41 | 5.08-15.24 | 25-51 | >183 |
| Herndon silt loam (Hn) | 0-158 | 1.52-5.08 | >152 | >183 |
| Hiwassee loam (Hw) and Hiwassee sandy clay | 0-178 | 1.52-5.08 | >152 | >183 |
| Masada fine sandy loam (Ma) | 0-25 | 5.08-15.24 | >152 | >183 |
| | 25-183 | 1.52-5.08 | | |
| Mecklenburg loam (Me) and Mecklenburg clay loam | 0-20 | 1.52-5.08 | >152 | >183 |
| | 20-64 | 0.15-0.51 | | |
| | 64-91 | 1.52-5.08 | | |
| Nason silt loam (Na) | 0-127 | 1.52-5.08 | 102-152 | >183 |
| | 127-137 | 0.0-0.15 | | |
| Oakboro variant silt loam (Oa) | 0-117 | 1.52-5.08 | 102-152 | 30-61 |
| Riverview loam (Rv) | 0-99 | 1.52-5.08 | >152 | 91-152 |
| Skyuka fine sandy loam (Sk) | 0-23 | 5.08-15.24 | >152 | >183 |
| | 23-183 | 1.52-5.08 | | |
| Tatum silt loam (Ta) | 0-107 | 1.52-5.08 | 102-152 | >183 |
| | 107-117 | 0.0-0.15 | | |
| Tatum-Badin complex (Tb) | 0-107 | 1.52-5.08 | 51-152 | >183 |
| Tatum soil (50%) | 107-152 | 0.0-0.15 | | |
| Badin soil (40%) | | | | |
| Udorthents (Ud) | 0-152 | 0.15-5.08 | >152 | >183 |
| Uwharrie silt loam (Uh) | 0-178 | 1.52-5.08 | >152 | >183 |
| Uwharrie-Nason-Tatum complex (Un) | 0-152 | 1.52-5.08 | 51->152 | >183 |
| Uwharrie soil (45%) | | | | |
| Tatum soil (25%) | | | | |
| Nason soil (20%) | | | | |
| Uwharrie-Tatum complex (Ut) | 0-152 | 1.52-5.08 | 102->152 | >183 |
| Uwharrie soil (45%) | | | | |
| Tatum soil (40%) | | | | |

through the GIS manipulation of the elevation data. Flow direction is used to determine the accumulated number of cells that flow into other cells (Jenson and Domingue, 1988). The accumulated number of cells draining into a single cell is multiplied by the area of a single cell (30 m \times 30 m for this research). Additionally, all cells were considered to flow into themselves; therefore no cell would have an input value of zero for calculation of the wetness index equation.

SCS soil maps for the study area were digitized into ARC/INFO. Soil interpretations for the soil types present in the study area were used to derive information about the various soil parameters used to calculate the wetness index. Specific information regarding soil depth (depth to bedrock, depth to water table, depth to impermeable barrier), soil hydraulic conductivity (permeability), and soil horizon boundaries, and variable permeability were extracted from SCS soil interpretations and input into the GIS database to be associated relationally with mapped soil types. In the GIS environment, each mapped unit of a certain soil type is assumed to have uniform type and physical characteristics. Figure 3 is a map of the soil types of the study area and Table II lists the soil attributes related to each soil type that were encoded into the GIS. The values for soils that are listed as soil complexes are derived from the SCS interpretations for the individual soil types, and reflect the combined maximum and minimum possible values for all of the constituent soil types of the complex. The soil parameters, expressed as ranges in Table II, constitute a potential source of variability in the calculation of the wetness index.

Depth to bedrock or to an impermeable subsoil layer is most commonly used to estimate soil depth. Alternatively, Phillips (1990) used the depth to a seasonally high water-table to estimate soil depth. His approach assumes that downward soil transmissivity is effectively prevented by the water-table. Both water-table and bedrock data are available for the study area from the SCS soil interpretations. The

Table III. Hydraulic conductivity by soil texture class (From Wolock *et al.*, 1989; cf. Rawls *et al.*, 1982)

| Soil texture class | Saturated hydraulic conductivity (cm h ⁻¹) |
|-------------------------------|--|
| Sand | 21.00 |
| Loamy sand | 6.11 |
| Sandy loam | 2.59 |
| Loam | 1.32 |
| Silt loam | 0.68 |
| Muck | 15.00 |
| Fine sandy loam | 3.00 |
| Mucky peat | 14.00 |
| Gravelly loam | 3.00 |
| Gravelly loamy sand | 7.00 |
| Channery silt loam | 1.00 |
| Variable | 1.00 |
| Mucky loamy fine sand | 17.00 |
| Channery loam | 1.50 |
| Complex | 1.00 |
| Very gravelly sandy loam | 3.50 |
| Peat | 12.00 |
| Channery very fine sandy loam | 3.00 |
| Coarse sand | 21.00 |
| Fibric | 10.00 |
| Gravelly sandy loam | 3.50 |
| Sandy clay loam | 0.43 |
| Clay loam | 0.23 |
| Silty clay loam | 0.15 |
| Sandy clay | 0.12 |
| Silty clay | 0.09 |
| Clay | 0.06 |
| Mucky loam | 5.00 |

Table IV. Variables used for the calculations of the topographic wetness index

| Trials | Parameters |
|--------|---|
| WT-1 | Assumes spatially uniform soil properties |
| WT-2 | Uses minimum SCS values summed by horizon |
| WT-3 | Uses median SCS values summed by horizon |
| WT-4 | Uses maximum SCS values summed by horizon |
| WT-5 | Assumes uniform hydraulic conductivity (using literature-derived values) to minimum depth |
| WT-6 | Assumes uniform hydraulic conductivity (using literature-derived values) to median depth |
| WT-7 | Assumes uniform hydraulic conductivity (using literature-derived values) to maximum depth |

bedrock data are used to estimate soil depth. However, the depth to a seasonally high water-table was used for those soil types which exhibited high water-tables.

Phillips (1990) indicated that one can use minimum, maximum or median values in computing the wetness index without producing significant differences in the relative values of the index, provided that consistent implementation rules are followed. In this research, the index was calculated using minimum, maximum and median values, and the resulting maps were compared for changes in magnitude and spatial variability.

In soil interpretations, maximum values are sometimes expressed as 'greater than' some amount. In such cases, the 'greater than' terminology and the corresponding values are used to estimate maximum depth. Likewise, the wetness index calculations for soils that only have one depth value use the value for minimum, maximum and median computations. The index was calculated to a maximum soil depth of 152 cm because this was the maximum value used in SCS interpretations. For soils exhibiting a seasonally high water-table, the median water-table depth was used to estimate minimum effective soil depth for moisture transmissivity.

Permeability data are used to estimate hydraulic conductivity. Minimum, median or maximum permeability values are used with the corresponding minimum, median or maximum depth to bedrock or water-table values. Because transmissivity is expressed as the sum of permeability for a horizon multiplied by the horizon thickness, any depth to bedrock or water-table beneath an impermeable layer is not included in the calculations. Transmissivity values are calculated consistently using minimum, maximum or median permeability (depending upon which is used for the depth parameter) to the stated depth or the depth of an impermeable layer.

The index calculation can be simplified if each soil type is assumed to have uniform hydraulic conductivity throughout its profile. In such cases, the wetness index is calculated using Equation 2 rather than Equation 3 to estimate soil transmissivity. Wolock (1988) estimated a uniform hydraulic conductivity based upon soil texture classifications and literature-derived information about texture. Table III lists soil texture classifications and the associated hydraulic conductivity values as used by Wolock (1988) and Wolock *et al.* (1989) derived from Rawls *et al.* (1982). Wolock (1988) used the median depth to bedrock to estimate soil depth for a soil type. Wolock's (1988) technique for estimating soil depth and soil hydraulic conductivity for the wetness index is compared with the indices calculated by summing transmissivity values within the horizons for a soil depth.

Finally, soil depth and hydraulic conductivity are considered to be uniform if no soil data are available for a study area (Brown, 1992). In such a case the wetness index equation is calculated as:

$$WT = \ln [A / \tan B] \quad (5)$$

Aggregated over a broad (i.e. non-hillslope) region, the assumption of uniform soil properties throughout the study area effectively averages soil variations. The assumption of uniform soils in broad-scale topographic modelling is not necessarily unreasonable. General soil properties can be related to landscape position in those instances where no soil information is available and an assumption of uniform soils may not

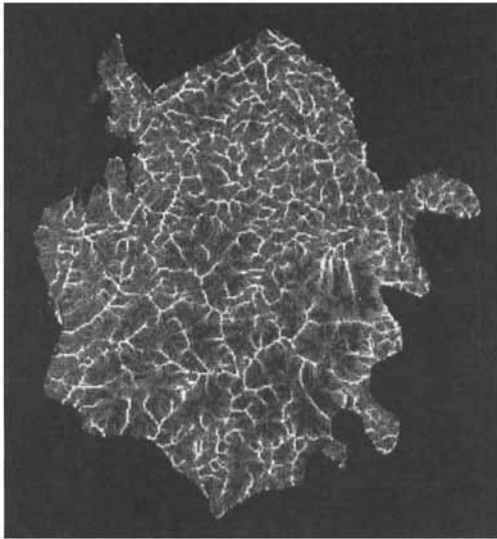
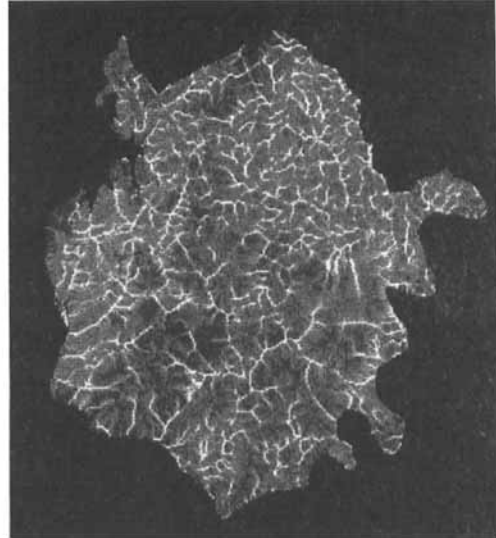
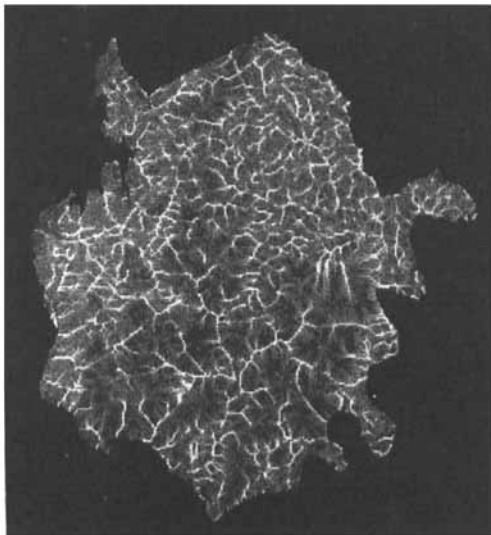
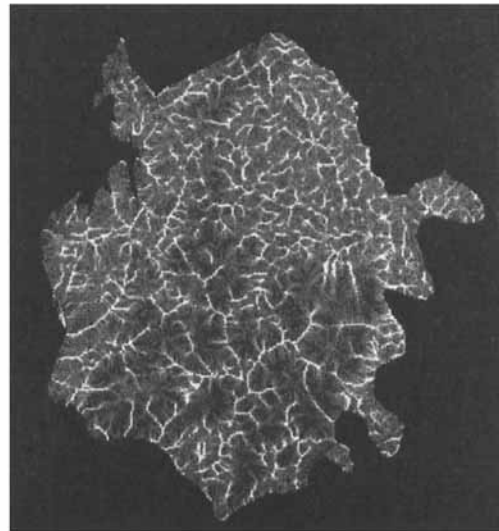
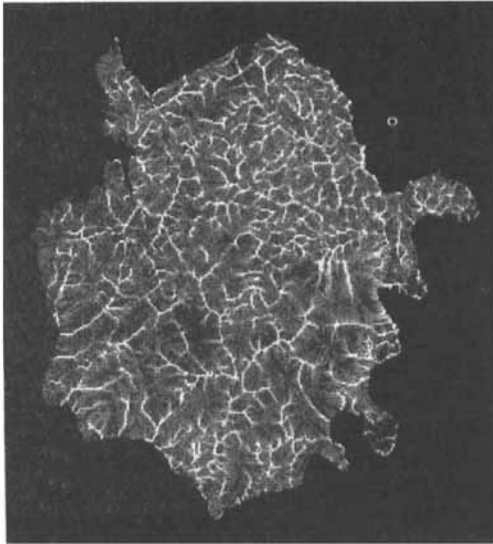
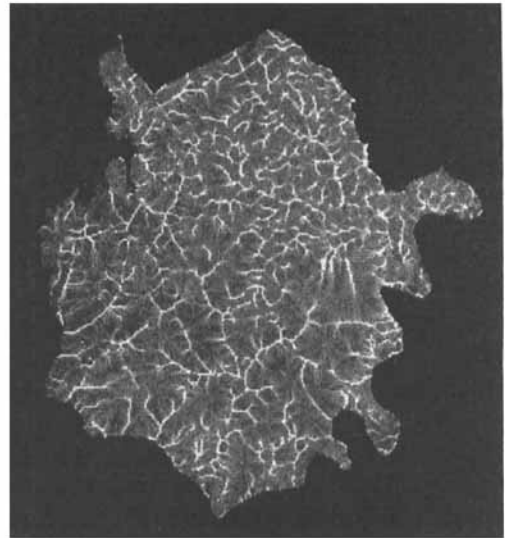
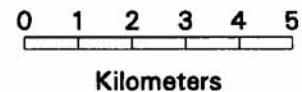
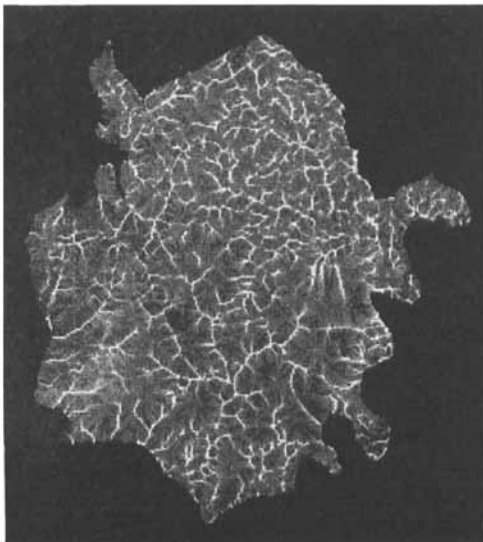
a. Trial WT-1**b. Trial WT-2****c. Trial WT-3****d. Trial WT-4**

Figure 4. (a–g) Wetness potential for each of the seven trials listed in Table IV. Brighter areas represent greater wetness potentials

be appropriate. In the Piedmont setting of this research, deeper, drier soils are generally found at higher topographic positions, whereas wetter soils are found in the valleys and along drainage pathways. However, local variations in soils that are not a function of topographic position will be absent from the calculations of the index.

The wet index was computed through seven different trials to assess the variation in the spatial pattern

e. Trial WT-5**f. Trial WT-6****g. Trial WT-7****Figure 4**

of the index as a consequence of user decisions in approaches to soil estimation. Table IV lists the seven trials that were generated and indicates which soil parameters were varied in each computation of the wetness index.

Inherent errors can exist within the representation of base variables entered into the GIS and such errors

can be propagated through the analyses as a result of operational errors (Walsh *et al.*, 1987). Inherent error is defined as error associated with source documents and the interpretation of these documents. It is produced as a consequence of transforming the three-dimensional Earth into a two-dimensional map in which landscape features and locations are characterized at some abstracted level of reality. Soil types are mapped through approaches that generalize reality. As a result, soil maps reduce in representation the spatial variability of reality, thereby introducing a degree of inherent error as a consequence (Buol *et al.*, 1989). Maps and/or digital data layers of selected physical characteristics of soils are created through the recording of soil type information and the redrawing of boundaries through automated approaches. Errors inherent in the soil type information are, therefore, present within derived soil layers of associated physical characteristics. Studies by Zhou *et al.* (1991) and Maclean *et al.* (1993) indicate that significant variability between mapped soil types and field samples remains a problem in the use and interpretation of soil data within analyses, including studies involving GIS. Because mapped soil units usually contain inclusions of other, often very different, soil types, one 30 m \times 30 m grid cell used in raster-based GIS modelling cannot represent the true variability of that soil occurring on a complex landscape as a result of data collection approaches and data aggregation strategies (Walsh, 1985). Additionally, soils vary in three dimensions and rarely does a mapped soil unit exhibit constant profile characteristics throughout its mapped areal extent. Likewise, the boundaries between soil types on a soil map suggest discrete representations of what is in reality a 'fuzzy' boundary. The SCS recognizes the inherent spatial variability of soil characteristics and addresses this concern by presenting quantitative information on soil characteristics as ranges that capture the variability of a mapped soil type, with annotated information provided regarding the size of inclusions mapped and not mapped. Finally, because SCS data are presented in ranges, the potential for interpretive error is introduced as a consequence of how the data are reported and used, regardless of whether the data are accurate or appropriate for the intended analyses. Such error is manifested spatially by the fact that the reported ranges in the SCS soil interpretations vary in magnitude among soil types.

METHODS

Data regarding the various parameters of the model were collected and organized within the GIS database. For each of the trials, the index was computed and mapped for comparison of the spatial distributions (Figures 4a–g). Lighter grey tones on the maps indicate higher index values and hence greater soil moisture potential. All of the maps indicate higher wetness potential values at topographic depressions, because natural drainage patterns yield zones of moisture accumulation. Similarly, higher elevations exhibit lower wetness potential values because water would be less likely to accumulate at those locations.

The index values for the study area were exported by cell coordinates (to maintain correct spatial position of cells within the data matrix) into the SAS statistical software package. A random sample of 2460 cells (approximately 5 per cent of the study area) was extracted from the population for statistical analysis. Pearson's correlation coefficients were calculated for the seven trials to measure the strength of the linear relationship between each pair of index calculations. Correlation analysis is a useful statistic for map comparison, particularly when the mapped classes are represented as interval or ratio data, because statistical comparison of multiple inputs is possible (Unwin, 1981). Least-squares regression was also used with several pairs of calculations of the wetness index to model the response of one calculation to variations in the calculations of each of the other trials. This technique involves regressing data from one calculation with data from another trial, thereby generating an equation that predicts the response of the second trial to changes in the first trial. The observed value for each grid cell is subtracted from the predicted value for that same grid cell (as derived by the model associated with each trial) to produce a map of differences between the regressed model and the actual index calculations. In essence, the resultant residuals from the regression reflect the variability in computation of the two index trials. Positive residuals reflect overprediction by the modelled wetness index with regard to another trial, whereas negative residuals reflect underprediction. Maps of the residuals are used to make generalizations about how and why the different computations of the wetness index vary spatially. By comparing the maps of residuals with maps of other biophysical features (e.g. vegetation distributions, landforms, geology, hydrography), one can begin to

Table V. Correlation matrix of trials associated with variations in the manner of soil estimation for the calculation of the wetness index. All correlations and statistical tests are significant at the 0.0001 confidence level

| Trials | WT1 | WT2 | WT3 | WT4 | WT5 | WT6 | WT7 |
|--------|-------|-------|-------|-------|-------|-------|-------|
| WT1 | 1.000 | 0.949 | 0.973 | 0.989 | 0.938 | 0.958 | 0.958 |
| WT2 | | 1.000 | 0.985 | 0.968 | 0.926 | 0.900 | 0.875 |
| WT3 | | | 1.000 | 0.989 | 0.909 | 0.909 | 0.897 |
| WT4 | | | | 1.000 | 0.925 | 0.937 | 0.932 |
| WT5 | | | | | 1.000 | 0.986 | 0.967 |
| WT6 | | | | | | 1.000 | 0.995 |
| WT7 | | | | | | | 1.000 |

assess which factors might be associated with significant divergences in the performance of the model outputs (Thomas, 1968; Unwin, 1981; Brown *et al.*, 1994).

RESULTS AND DISCUSSION

Table V presents a matrix of correlation coefficients for the seven trials evaluated in this research. The following sections examine each of the seven trials with respect to the different approaches used to estimate the soil factors that were integrated with topographic information within the calculation of the wetness index.

Scenario I: soil parameters (WT-2) vs. uniform soil characteristics (WT-1)

Normally, soil information should be used to compute the wetness index if adequate data are available. If not, the common practice is to assume uniformity in soil characteristics. Table V indicates correlations ranging from 0.938 to 0.989 between maps of index values generated with and without soil parameters. Although soils do vary significantly in the study area, those variations are generally associated with topographic position. Thus, the spatial variation in soil properties does not affect relative index value calculations, because landscape position is already a fundamental assumption of the drainage area component of the wetness index calculation defined through the DEM. However, local depressions in the landscape may account for some of the differences between the derived index values.

One cannot conclude absolutely from these data that soil information is unnecessary to calculate the index. If the index is to be used to calculate absolute runoff values, soil information should be incorporated. Alternatively, the index may not perform well without soil data in areas where subtle topographic variation can lead to significant soil differences. In the portion of the Uwharrie National Forest evaluated, the wetness index performed well without using soil parameters in its calculations.

WT-1 was regressed against trial WT-2 (using minimum soil values) and residuals were mapped (Figure 5). The mapped residuals were assessed through the calculation of Moran's index of spatial autocorrelation, a measure of the ordering of data values as a consequence of spatial location (Griffith, 1987). The presence of spatial autocorrelation indicates that values are ordered as a consequence of spatial location. A high spatial autocorrelation (Moran's $I = 0.851$) characterized the mapped residuals for trial 1 versus trial 2, thereby suggesting that the presence of different soil types affected the mapped spatial pattern of the wetness index. From Figure 5, an assumption of uniformity of soil type (WT-1) underpredicts soil moisture potential with respect to WT-2 (using soil parameters) in much of the study area. This may result from specific soil types within the study area, such as the Enon-Zion soils, having slow permeability and therefore a greater potential for saturation than other soils in the region. A model calculation that assumes uniformity of soil response underestimates soil saturation with respect to the manner in which the wetness index is calculated.

Similarly, WT-1 overpredicts soil moisture potential for areas mapped with more permeable and deeper soil types. The Skyuka, Uwharrie, Georgeville and Riverview soil series have moderate permeability but are

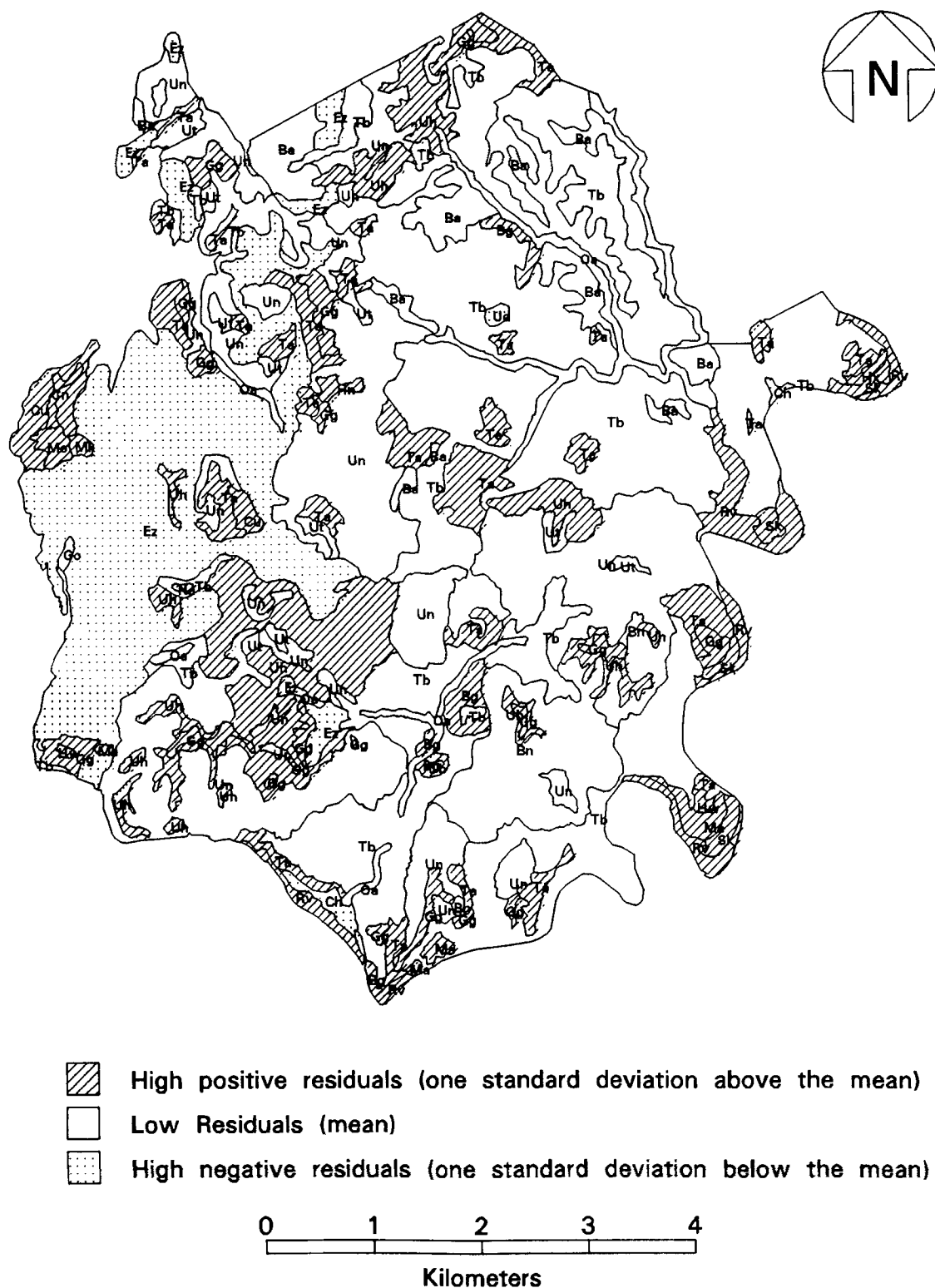


Figure 6. Regression residuals calculated for WT-4 versus WT-2. This map indicates areas where WT-4 (using maximum SCS values in the calculation) over- and underpredicts the wetness index with respect to WT-2 (using minimum SCS values)

very deep soils, making areas mapped with those soil types less likely to be saturated. Thus, soil moisture potential is overpredicted in those areas when soil uniformity is assumed. Elevation characteristics do not appear to influence the residuals, because the north part of the study area (least rugged) and south (most rugged) have low and comparable residuals.

Scenario II: minimum, median or maximum values for soil depth and permeability (WT-2, WT-3 and WT-4)

The index was calculated by alternately using minimum (WT-2), median (WT-3) and maximum (WT-4) values where the soil depth and permeability variables were reported as ranges in the SCS soil interpretations. To maintain consistency, minimum, median and maximum values were used for soil depth and permeability in each respective calculation of the index. The correlation coefficients presented in Table V indicate that minimum, maximum or median values for soil parameters expressed as ranges (depth and permeability) produce highly correlated wetness index values. The uniformly high correlation coefficients support Phillips' (1990) assertion that as long as minimum, median or maximum values are used consistently, the resulting maps will not vary substantially.

Although all of the maps created, using different depth criteria, appear highly correlated, the trial pairs that correlated least (WT-2 and WT-4: $r = 0.968$) were regressed to examine the residuals. WT-4 (using maximum values) were regressed against WT-2 (using minimum values), and the residuals were mapped (Figure 6). The mapped residuals displayed high spatial autocorrelation (Moran's $I = 0.826$), suggesting a spatial explanation for the variability in the wetness index responses. Wetness potential for areas mapped as Chewacla and Udorthents soils are underpredicted when the maximum values are used (WT-4). An examination of the soil characteristics (Table II) reveals that these two soil types have relatively wide ranges between minimum values and maximum values when compared to the other soils. Soil depths for the Chewacla series range from 15 to 152 cm, whereas the permeability for Udorthents ranges from a very low 0.15 cm h^{-1} to a moderate 5.08 cm h^{-1} . As such, the wetness index computations for areas containing these soils is more sensitive to the values used in the computation.

A number of areas mapped, for example, Uwharrie, Georgeville, Cullen, Mecklenburg, Riverview and Skyuka, are overpredicted by WT-4 (using maximum values) with respect to WT-2 (using minimum values). These soils have a depth extending to 152 cm, but the SCS interpretations indicate no depth range for the soils. Therefore, generation of minimum, median and maximum values for the specific soil types use the same value of 152 cm in the calculation of the wetness index. The lack of a data range in the SCS depth to bedrock values produces a relative overprediction of wetness by WT-4 when compared to WT-7.

Scenario III: uniform hydraulic conductivity (WT-2 to WT-4) vs. summing soil permeability by horizon depth (WT-5 to WT-7)

The maps created using values for soil hydraulic conductivity, based upon soil texture classes presented in Table III, were compared to maps calculated using Equation 3 to estimate soil transmissivity to a given soil depth. Although it is preferable to use published soil parameters when calculating wetness indices, texture-based hydraulic conductivity values can be substituted for permeability data, either when such

Table VI. Difference between SCS permeability values and literature-derived hydraulic conductivity for soil texture classes

| Soil series | SCS range (cm h^{-1}) | Value by texture class (cm h^{-1}) |
|-----------------------------|---|--|
| Badin channery silt loam | 1.52–5.08 | 1.00 |
| Chewacla silt loam | 1.52–5.08 | 0.68 |
| Cullen clay loam | 1.52–5.08 | 0.23 |
| Goldston channery silt loam | 5.08–15.24 | 1.00 |
| Riverview loam | 1.52–5.08 | 1.32 |
| Skyuka fine sandy loam | 5.08–15.24 (to 23 cm) 1.52–5.08 (23 to 183 cm) | 3.00 |

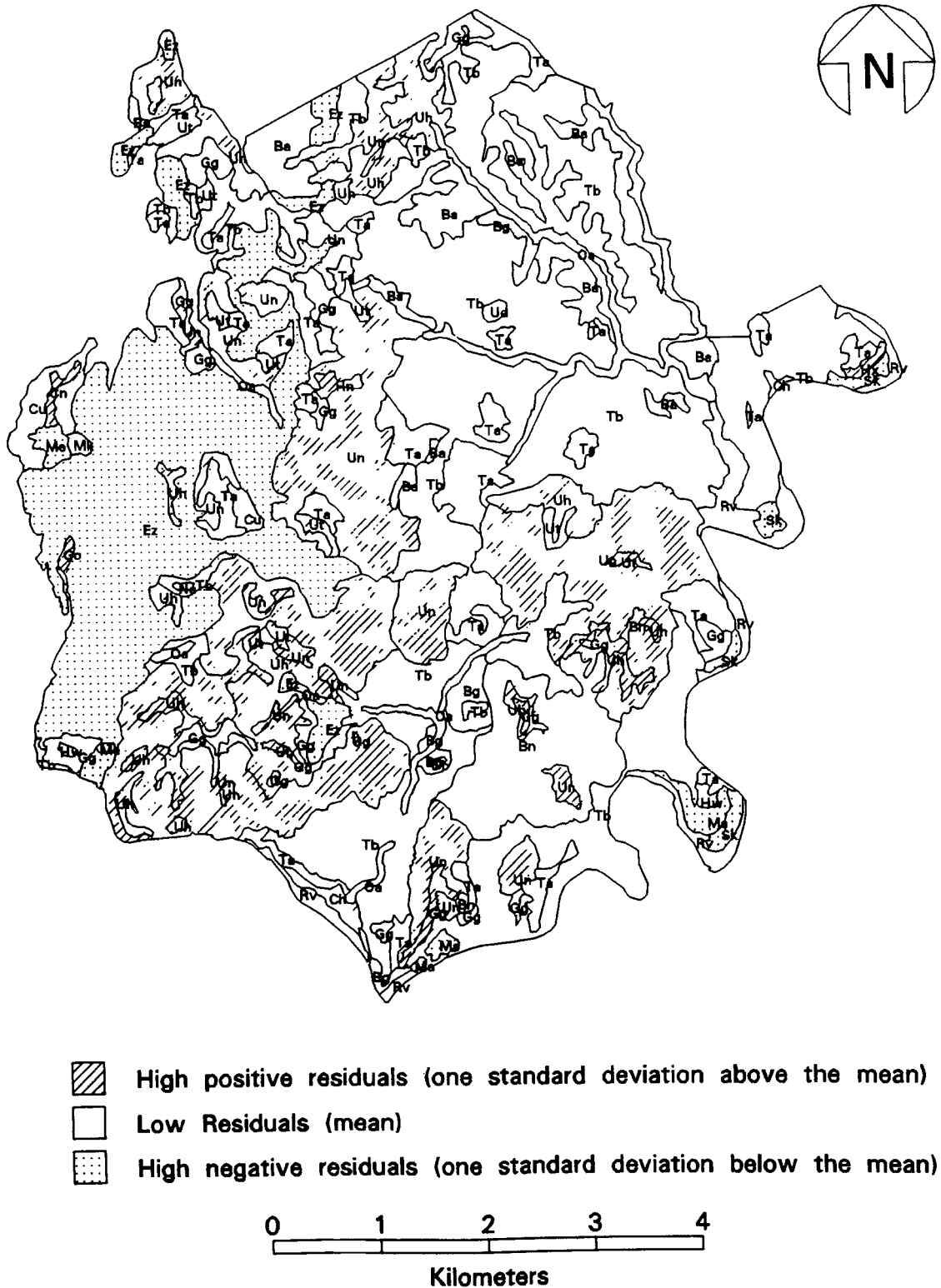


Figure 7. Regression residuals calculated for WT-7 versus WT-4. This map indicates where WT-7 (using Rawls *et al.* (1982) textural class data) over- and underpredicts the wetness index with respect to WT-4 (using SCS data)

data are unavailable or impractical to use. Table VI shows differences in the estimation of soil hydraulic conductivity in the calculation of the wetness index when the data are secured from alternative literature-derived sources.

The soil data presented in Table VI for Badin, Chewacla and Cullen soils indicate the same SCS permeability range, although each has a very different value based upon its texture. Similarly, Badin and Goldston soils have differing SCS ranges but the same hydraulic conductivity according to the texture class. Using texture class information to assign hydraulic conductivity does not address the complexity of soils that results from permeability differences among soil horizons.

Trials WT-5, WT-6 and WT-7 each calculated the wetness index using texture-based hydraulic conductivity values with minimum, median and maximum depths, respectively. The resultant maps correlated highly with each other. Regression analyses also reported high R^2 values that ranged from 0.909 to 0.932. The analyses suggest that the approach advocated by Rawls *et al.* (1982), involving texture-based soil hydraulic conductivity values, does not significantly alter the computations of the wetness index. However, these pairs of trials do not correlate as highly as previously assessed results.

Maps were generated of the residuals for the regression of each of the trial pairs (WT-5, WT-6 and WT-7) calculated using the texture-based hydraulic conductivity against those using the SCS data. Figure 7 is a map of the residuals of the regression of WT-7 against WT-4. The residuals were highly autocorrelated (Moran's $I = 0.893$), indicating a high spatial ordering of the residuals. Soils such as Enon-Zion have high negative residuals, indicating that those areas are underpredicted by the models using the textural class data. Because Enon-Zion soils are considered to be a soil complex in the Rawls *et al.* (1982) scheme, the hydraulic conductivity was determined to be 1.00 cm h^{-1} , which is significantly higher than the ranges expressed for the same soils in the SCS interpretations. The Enon-Zion soils appear to have lower wetness potential when the index is calculated using the Rawls *et al.* (1982) criteria than when using the SCS information.

Uwharrie, Tatum and Udorthents soils have high positive residuals, thus appearing overpredicted by the wetness index calculated using the texture class hydraulic conductivity data. These variations also arise from the differences between the SCS ranges and the values presented in Table IV. In these cases, the hydraulic conductivity values were smaller than suggested by the SCS, leading to the overestimation of soil saturation potential for those areas.

One major problem with using any texture-based values for hydraulic conductivity is that soil is rarely texturally homogeneous throughout a profile. A soil may be classified in a texture class that has a certain permeability, yet the presence of any texturally more or less permeable horizon will skew the wetness index calculation towards values that do not adequately represent soil conditions. The technique of mapping regression residuals is used to highlight areas within the study area that are least explained by the derived model and therefore sensitivity to variations in the input data.

CONCLUSIONS

This study examines the differences that are introduced in a wetness index when its soil parameters are derived through alternative approaches. The wetness potential maps for the study area, generated for seven trials representing differences in estimating soil conditions, correlated closely with each other, suggesting that the choice of parameters in the derivation of the index did not significantly affect the data values for the study area. The index values calculated without using soil information also correlated well with those that did include soil parameters. However, maps of residuals of pair-wise regressions for the seven trials indicate that spatial variability exists as a consequence of the approach used to estimate the soil parameters. These differences relate specifically to the soil characteristics in the areas with either high or low residuals. The assumption of soil uniformity led to underprediction or overprediction of wetness potential in areas with variable soils.

Maps of regression residuals created using literature-derived soil criteria were found to correlate closely with maps created using SCS data. Equation 3 should be used if the appropriate input data are available, because it permits the maximum specificity with regard to soil characteristics. For input into the model, minimum, median and maximum values can each be used for those parameters for which the data are expressed

as a range. The SCS parameters used in this research represent a level of soil generalization. Because soils are ultimately more spatially variable than is implied by the mapped units, any index that uses soil data will be subject to a considerable amount of uncertainty and inherent error.

This research demonstrates the potential for spatial variability in the results of distributed parameter models as a consequence of parameter estimation approaches. The mapping of regression residuals is a useful tool to highlight those areas that are particularly sensitive to different methods of parameter estimation for input into a model. Those areas with high positive or negative residuals are the areas in which less confidence can be placed in the model outputs, because the data values deviate most from the derived model.

Maps of residuals can be used to identify areas in which input data must be more accurately defined. For examples, this research suggests that the soil parameters defined for the Enon-Zion series can create significant variations in the wetness index output depending upon how the parameters are estimated. By examining the spatial pattern of the residuals, additional parameters that might be integrated into the model, such as rainfall distribution or vegetation cover, can be hypothesized. The limitations of the model and the input data required to calculate it can therefore be used to refine the model calculations.

REFERENCES

- Band, L. E. and Wood, E. F. 1988. 'Strategies for large-scale, distributed hydrologic simulation', *Applied Mathematics and Computation*, **27**, 23–37.
- Beven, K. J. and Kirkby, M. J. 1979. 'A physically based, variable contributing area model of basin hydrology', *Hydrological Sciences Bulletin*, **24**, 43–69.
- Brown, D. G. 1992. *Topographical and Biophysical Modeling of Vegetation Patterns at Alpine Treeline*, unpublished Ph.D. Dissertation, University of North Carolina-Chapel Hill, 239 pp.
- Brown, D. G., Cairns, D. M., Malanson, G. P., Walsh, S. J. and Butler, D. R. 1994. 'Remote sensing and GIS techniques for spatial and biophysical analyses of Alpine treeline through process and empirical models', in Michener, W. K., Brunt, J. W. and Stafford, S. G. (Eds), *Environmental Information Management and Analysis*, Taylor and Francis, New York, 457–485.
- Buol, S. W., Hole, F. D. and McCracken, R. J. 1989. *Soil Genesis and Classification*, Iowa State University Press, Ames, 446 pp.
- Conley, J. F. 1962. *Geology of Albemarle Quadrangle, North Carolina*, Regional Geology Series 2, Geological Survey Section, Department of Natural Resources and Community Development, Raleigh, NC.
- Davis, F. W. and Dozier, J. 1990. 'Information analysis of a spatial database for ecological land classification', *Photogrammetric Engineering and Remote Sensing*, **56** (5), 605–613.
- Goodchild, M. F. 1992. 'Geographical information science', *International Journal of Geographical Information Systems*, **6** (1), 31–45.
- Griffith, D. A. 1987. *Spatial Autocorrelation: A Primer*, Resource Publications in Geography, Association of American Geographers, Washington, DC, 82 pp.
- Jenson, S. K. and Domingue, J. O. 1988. 'Extracting topographic structure from digital elevation data for geographic information system analysis', *Photogrammetric Engineering and Remote Sensing*, **54** (11), 1593–1600.
- Joao, E. M. and Walsh, S. J. 1992. 'GIS implications for hydrologic modeling: simulation of nonpoint pollution generated as a consequence of watershed development scenarios', *Computers, Environment and Urban Systems*, **16**, 43–63.
- Macleon, A. L., D'Avello, T. P. and Shetron, S. G. 1993. 'The use of variability diagrams to improve the interpretation of digital soil maps in a GIS', *Photogrammetric Engineering and Remote Sensing*, **59** (2), 223–228.
- Moore, I. D., Grayson, R. B. and Ladson, A. R. 1991. 'Digital terrain modelling: a review of hydrological, geomorphological, and biological applications', *Hydrological Processes*, **5**, 3–30.
- O'Loughlin, E. M. 1986. 'Partition of surface saturation zones in natural catchments by topographic analysis', *Water Resources Research*, **22**, 794–804.
- Phillips, J. D. 1990. 'A saturation-based model of relative wetness for wetland identification', *Water Resources Bulletin*, **26**, 333–342.
- Rawls, W. J., Brakensiek, D. L. and Saxton, K. E. 1982. 'Estimation of soil water properties', *Transactions of the American Society of Agricultural Engineers*, **25**, 1316–1320.
- Romanowicz, R., Beven, K., Freer, J. and Moore, R. 1993. 'TOPMODEL as an application module within WIS', in Kovar, K. and Nachtnebel, H. P. (Eds), *HydroGIS 93: Application of Geographic Information Systems in Hydrology and Water Resources*, (Proceedings of the Vienna Conference. April 1993), International Association of Hydrological Sciences, Wallingford, IAHS Publ. (211), 211–223.
- Thomas, E. N. 1968. 'Maps of residuals from regression', in Berry, B. J. L. and Marble, D. F. (Eds), *Spatial Analysis: a Reader in Statistical Geography*, Prentice-Hall, Englewood Cliffs, NJ, 326–352.
- Unwin, D. 1981. *Introductory Spatial Analysis*, Methuen, New York, 212 pp.
- Walsh, S. J. 1985. 'Geographic Information Systems for natural resource management', *Journal of Soil and Water Conservation*, **40**, 202–205.
- Walsh, S. J., Lightfoot, D. R. and Butler, D. R. 1987. 'Recognition and assessment of error in geographic information systems', *Photogrammetric Engineering and Remote Sensing*, **53** (10), 1423–1430.
- Walsh, S. J., Butler, D. R., Brown, D. G. and Bian, L. 1990. 'Cartographic modelling of snow avalanche path location within Glacier National Park, Montana', *Photogrammetric Engineering and Remote Sensing*, **56** (5), 615–621.
- Walsh, S. J., Brown, D. G., Bian, L. and Allen, T. R. 1994. 'Effects of spatial scale on data certainty: an assessment through data

- dependency and sensitivity analyses', *Proceedings, International Symposium on Spatial Accuracy of Natural Resource Data Bases*, American Society for Photogrammetry and Remote Sensing, Williamsburg, Virginia, in press.
- Wolcock, D. M. 1988. *Topographic and Soil Hydraulic Control of Flow Paths and Soil Contact Time: Effects on Surface Water Acidification*. Unpublished Ph.D. Dissertation, University of Virginia.
- Wolcock, D. M., Hornberger, G. M., Beven, K. J. and Campbell, W. G. 1989. 'The relationship of catchment topography and soil hydraulic characteristics to lake alkalinity in the northeastern United States', *Water Resources Research*, **25**, 829–837.
- Wood, E. F., Sivapalan, M., Beven, K. and Band, L. 1988. 'Effects of spatial variability and scale with implications of hydrologic modeling', *Journal of Hydrology*, **102**, 29–47.
- Zhou, H. Z., MacDonald, K. B. and Moore, A. 1991. 'Some cautions on the use of geographic information systems (GIS) technology to integrate soil site and area data', *Canadian Journal of Soil Science*, **71**, 389–394.